An Adaptive and VANETs-based Next Road Re-routing System for Unexpected Urban Traffic Congestion Avoidance

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***Abstract*—Unexpected road traffic congestion caused by en-route events, such as car crashes, road works, unplanned parades etc., is a real challenge in today's urban road networks as it considerably increases the drivers' travel time and decreases travel time reliability. To face this challenge, this paper extends our previous work named Next Road Rerouting (NRR) by designing a novel vehicle rerouting strategy that can adapt itself to the sudden change of urban road traffic conditions. This is achieved through a smart calibration of the algorithmic and operational parameters of NRR without any intervention from traffic managers. Specifically, a coefficient of variation based method is used to assign weight values to three factors in the routing cost function of NRR, and the K-Means algorithm is applied periodically to choose the number of NRR enabled agents needed. This adaptive-NRR (a-NRR) strategy is supported by vehicular ad-hoc networks (VANETs) technology as this latter can provide rich traffic information at much higher update frequency and much larger coverage than induction loops used in the previously proposed static NRR. Simulation results show that in the city center area of TAPASCologne scenario, compared to the existing vehicle navigation system (VNS) and static NRR, our adaptive-NRR can achieve considerable gain in terms of trip time reduction and travel time reliability improvement.**

I. INTRODUCTION

Urban congestions often appear during peak hours when the surging number of vehicles greatly exceeds the capacity of the road network. Unlike normal or recurrent congestion, the one caused by en-route events (e.g. car crashes, road works and unplanned parades etc.) can lead to unexpected delays which even make drivers almost triple their planned travel durations to reach their destination on time [1]. This problem is becoming serious as Gross Domestic Product (GDP) grows [2], preventing cities or countries from achieving higher and more efficient growth of their economy.

To mitigate unexpected traffic congestions, we have previously [3] proposed a two-step vehicle rerouting strategy named "Next Road Rerouting (NRR)". As a first step of NRR, the vehicles affected by the occurred event are rerouted to one of their available oncoming roads. This suggested "next road" has the highest potential to help these vehicles to avoid the oncoming congestion and drive closer to their destinations. In the second step, upon reaching the "next road", the rerouted vehicles use their vehicle navigation system (VNS) to compute the routes for the rest of their journeys.

Compared to the popular VNS, such as Google Maps or TomTom, and other relevant solutions from literature [9] [10] [11], NRR reroutes vehicles efficiently by only calculating the best "next road" rather than the entire route. Moreover, all the required information to perform this rerouting are locally available, which saves huge potential cost for obtaining global information. However, the calibration of the algorithmic and operational parameters of NRR needs to be done manually by experienced traffic managers. Additionally, the provider of information on road traffic conditions in NRR (i.e. induction loop) has limited update frequency (max 1min) and coarse granularity (only arterial roads are covered), preventing it from supplying sufficient information to allow making better rerouting decision.

For example, rerouting system in Figure 1 aims to balance traffic load locally, when vehicles are approaching the junction from road r_1 we can distinguish two cases as follows: in the first case, as shown in Figure 1 (a), the system will reroute the vehicles from r_1 to r_2, after a time duration t_1, as shown in (b), the system should reroute the vehicles from r_1 to r_3 but due to its slow update frequency ($T > t_1 + t_2$), the system's view stays at (a). Thus, the system keeps incorrectly rerouting the vehicles from r_1 to r_2. In the second case, as shown in Figure 1 (d), the system should reroute the vehicles from r_1 to r_3 because the latter has more capacity than r_2. However, due to its limited coverage for major roads, the system considers that r_2 has no traffic as in Figure 1 (e), and incorrectly reroute the vehicles into it. The results shown in both (c) and (f) reveal that the system has created another congestion without actually balancing the traffic.

The problems highlighted in Figure 1 can be found in another popular method for traffic information collection, floating car data (FCD), which is usually applied in VNS with 2-5 mins update frequency and arterial roads coverage. Vehicular ad-hoc networks (VANETs) is an emerging tech-

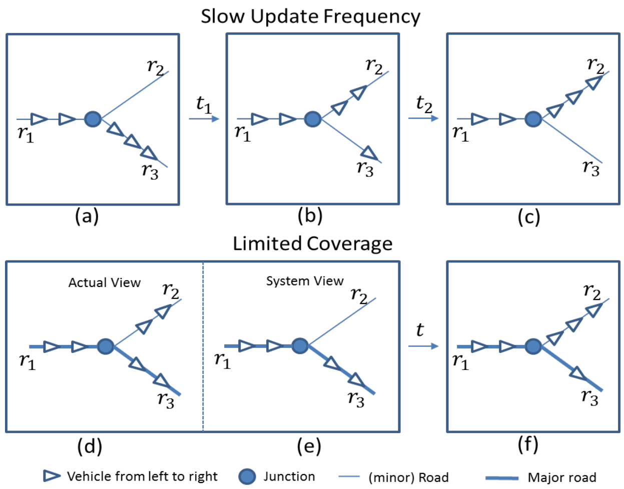

Fig. 1. The impact of slow update frequency and limited traffic information coverage on the rerouting decision.

nology that overcomes the above problems. Each vehicle in VANETs broadcasts its status (e.g. speed, heading, position, acceleration, etc.) at least every 0.1 second within one-hop transmission range (typically 300 meters). VANETs can also cover all areas where roads have vehicles running on. However, compared to driving safety and infotainment, little efforts only have been devoted by VANETs' research community to improve traffic management. Most of related solutions in the literature are not practical enough as they usually require the exchange of vehicles' routing decisions which violates the drivers' privacy. Moreover, the full route information can even be unknown for drivers traveling in new areas. Additionally, these solutions often need global traffic conditions which rely on the error-prone coordination mechanism among various local areas (i.e. the area covered by one hop transmission) of VANETs and often suffers from the non-line-of-sight problem around intersections.

To overcome the aforementioned limitations, this paper proposes adaptive-NRR (a-NRR) by introducing VANETs technology and incorporating an intelligent mechanism to calibrate the algorithmic and operational parameters of NRR to respond to real-time traffic changes. The contributions of this paper are listed as follows:

- **a-NRR fills the gap in the applications of VANETs for traffic management.** The philosophy of NRR is to accommodate various rerouting requests in multiple local areas simultaneously. VANETs can provide rich traffic information with high update frequency within a range that covers a local area (i.e. within one-hop transmission). Therefore, VANETs fits perfectly a-NRR needs so that the costly global traffic information can be avoided. Moreover, by using this technology, a-NRR needs drivers' destination only instead of their full route information, and vehicles' rerouting decision can be substantially improved by high-resolution traffic information and the non-line-of-sight problem can be mitigated through the RSU deployed at each intersection.
- **a-NRR can dynamically calibrate its algorithmic and operational parameters.** For algorithmic parameters, a-NRR uses the coefficient of variation to determine the importance of each factor in routing cost function. For operational parameters, a-NRR uses K-Means algorithm [17] to select the local areas which need to execute NRR in real-time. Thus, a-NRR can improve the traffic without any intervention from traffic managers.
- **a-NRR has more accurate distance estimation in routing cost function.** Since roads topologies do not change so often, instead of computing the Euclidean distance as in s-NRR and other heuristic algorithms, a-NRR calculates the shortest route cost for all possible origin/destination (O/D) pairs in a given map and resides this information in the server memory before computing rerouting decisions. Thus, a-NRR has more accurate estimation of the remaining travel distance and much faster memory access time than on-line computation time.

The rest of this paper is organized as follows. Section II summarizes related works on vehicles' route planning and smart routing system. Section III recaps the motivation and rerouting process of NRR. Section IV describes how a-NRR can adjust its algorithmic and operational parameters to the current traffic state. Section V illustrates our evaluation methodology whereas Section VI presents the obtained results and their analysis in comparison to s-NRR and VNS. Finally, Section VII draws the conclusion and outlines our future work.

II. RELATED WORK

A. Vehicle route planning

Theoretical works on vehicle route planning start from Dijkstra's Algorithm (DA) [4] which can find a route with the shortest travel distance to a vehicle's destination. A* algorithm [5] can speed up this process with much less search spaces using an estimation function. Both DA and A* belong to selfish routing which finds a least cost path for an O/D pair only. If all vehicles choose their routes selfishly, Wardrop's first principle [6] states that the best case is called "user equilibrium (UE)" where no one can unilaterally find a faster route, and no minimum travel time is guaranteed also. As Baress's Parodox describes [7], when adding a new road (or one road has just cleared its traffic because of green traffic light) to a UE congested network, it may actually increase the total travel time. According to Wardrop's second principle [6], system optimum (SO) is a result of traffic assignment in a given road network where minimum travel time for all vehicles is achieved. To progress from UE to SO, according to game theory, all vehicles need to work cooperatively to share and improve their route decisions. [8] has improved a SO algorithm so that it can avoid assigning few vehicles much longer route to gain global minimum travel time. Unfortunately, to the best of our knowledge, there is no dynamic traffic assignment algorithm that can give SO solution in polynomial time.

B. Smart routing system

With the development of related applied technologies (e.g. sensors, ICT enabled devices), many practical smart routing systems have been proposed in recent literature. T-Drive [9] uses massive historical GPS trajectories of taxi drivers in Beijing to learn how human intelligence can choose faster route in realistic urban scenarios. Participatory route planning proposed in [10] can minimize the urban traffic by using mobile devices to exchange and improve each vehicle's current route decision. VANETs has also shown its advantage in smart routing system, for example, CATE [11], has implemented and evaluated a system prototype to collect real-time traffic information globally and dynamically adjust vehicles' route plan to improve traffic in a complete VANETs environment. However, compared to the two typical VANETs applications, driving safety and infotainment [12], there are still lots of potential to tackle practical challenges when using VANETs to manage urban road traffic.

III. OVERVIEW OF NRR

A. Motivation

When an unexpected congestion occurs, a solution with timely response is highly required. We believe that the idea of always finding a complete route is the key reason of the incurred excessive cost because it requires loading the whole city map for each single rerouting request. For urban traffic congestion alleviation purpose, the top priority is to avoid the congestion rather than finding the full route solution for a given OD pair. Thus, designing a new practical congestion alleviation solution should have much potential to reduce the aforementioned extra cost caused by the idea of always finding a full route.

In face of an unexpected congestion, drivers intuitively update the next road to follow in their mind rather than the full route. Inspired from that, as shown in Figure 2, NRR divides a full city map into multiple connected local areas (i.e., agents). Each agent consists of a junction and all the roads directly connected to it. When unexpected congestions occur, the responsibility of each agent is to reroute the affected vehicles to balance its local traffic without significantly increasing their travel distance. Considering the fact that the roads connecting two neighboring agents are incoming for one and outgoing for the other, and taking advantage of natural traffic propagation, balancing the traffic locally (in one agent) will eventually result in balancing it globally. This fact can be inferred from the example and evaluation results presented in [3] and this paper.

There are two reasons to explain the two-step rerouting of NRR: first, balancing the traffic is a way to maximize the utility of road capacity, thus the congestion is highly mitigated; second, after being diverted to an uncongested area, the actual fastest route will have no obvious difference in time cost (mainly depends on the length of road rather than the traffic status) with the route suggested by VNS.

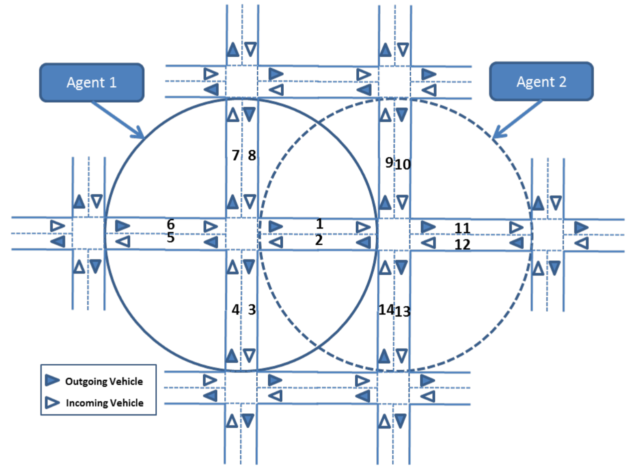

Fig. 2. Illustration of agents (local areas) in NRR

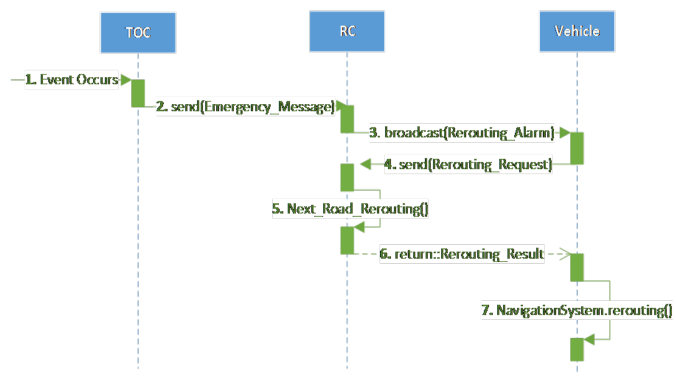

Fig. 3. Rerouting Process of NRR in UML sequence diagram

B. Re-routing process

The typical rerouting process is reviewed in Figure 3: when an en-route event occurs, (1) the Traffic Operation Center (TOC) verifies it and (2) activates NRR with a list of enabled agents; (3) a relevant road side unit (RSU) controlled by the regional computer (RC) broadcasts rerouting alarm to all vehicles located in the same agent; then these vehicles check whether the closed road is included in their current route plan; (4) if it is the case, each vehicle sends back a rerouting request with its intended destination location to the RSU; (5) RC uses the latest traffic information to calculate the best next road using NRR's routing cost function and (6) sends the result back to the requesting vehicle which takes it and enters the next road, then (7) it uses VNS to complete the rest of its journey.

C. Limitations

A practical solution for the implementation of static-NRR (s-NRR) is to build on the existing traffic light control systems (e.g. SCATS [23]) due to their high architectural similarity, but few limitations are still to be overcome in s-NRR. Firstly, in step 1, the operational parameter is chosen manually by experienced traffic managers. This process usually needs many time-consuming trials under various traffic congestion levels for each urban scenario. Secondly, in step 5, for the calculation of routing cost, the importance of each factor should be different for various rerouting requests rather than being fixed. Thirdly, road occupancy and estimated travel time have potential to be measured more accurately because both are derived from the degree of saturation which is the only measurement provided by induction loop. Finally, the estimated remaining distance is calculated using Euclidean distance. Considering the diversity of the topology of urban road networks, the accuracy of this calculation still needs to be improved.

IV. ADAPTIVE-NRR

To overcome the limitations of s-NRR, this section presents in detail how adaptive-NRR (a-NRR) can dynamically calibrate the algorithmic and operational parameters to the current traffic state.

A. Pre-requisite techonology

The pre-requisite technology of adaptive-NRR is VANETs which can provide real-time traffic information with full coverage, high resolution and update frequency to make timely adaptation possible in face of unexpected congestions. In a typical VANETs scenario, each vehicle broadcasts and receives "beacon" messages periodically to enable better awareness of the local traffic situation within its transmission range. In the two most widely recognized VANETs standards, this "beacon" message is called Cooperative Awareness Message (CAM) and is part of the "Facilities Layer" of ETSI ITS [13], or defined as "Basic Safety Message" in IEEE WAVE protocol stack [14]. A beacon message contains information about the speed, acceleration, position, heading etc, of a certain vehicle. It is broadcast at least 10 times per second. VANETs can also cover all areas where roads have vehicles running on. Most importantly, VANETs technology fits perfectly into local urban scenarios, especially in a-NRR system where a whole city map is processed separately and simultaneously in different local areas. This is because we surprisingly found that the length of up to about 90% of urban roads is within one-hop VANET transmission area which is typically 300 m [15] (could be up to 1000 m [14]).

This interesting conclusion is made from the statistics of various city maps from OpenStreetMap [22]. As shown in Table 1, we select a representative city from each continent (excluding Antarctica, because it has no big city with serious congestion problems) where citizens often experience heavy congestion in peak hours according to a well-recognized worldwide congestion report released by TomTom [16].

a-NRR maintains the major part of s-NRR's architecture (i.e. TOC connects multiple regional computers (RC) which are in charge of one or more NRR agents) with only one replacement of induction loops by VANETs. As shown in Figure 4, in s-NRR, the communication between the RSU and vehicles is in one-to-one manner only for rerouting confirmation. The same communication is now extended in a-NRR by adding one (RSU) to all (vehicles on one particular road) manner for traffic information collection. Another tip for on-site deployment is that the RSU should be placed in a higher location to avoid non-line-of-sight problem.

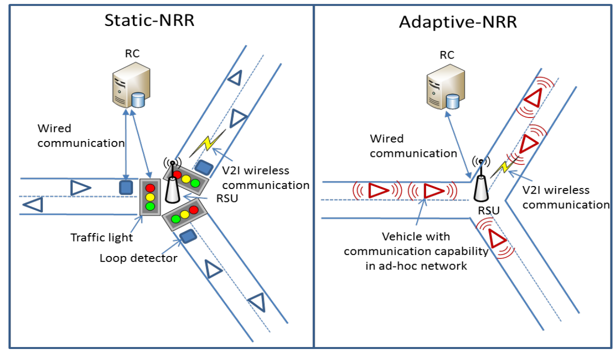

Fig. 4. The architecture of agent in s-NRR and a-NRR

B. Adaptive selection of the algorithmic parameters

The weight values allocation, which is the algorithmic parameter in NRR, shows how important each factor is for the final rerouting decision. In NRR, all factors in the next road cost function vary from time to time (road occupancy, estimated travel time) and from vehicle to vehicle (estimated remaining distance), thus, a good weight value allocation should be variable for different rerouting requests rather than fixed as in s-NRR. In the next road selection, for a particular factor of a set of available next road choices, the greater the variation is, the more important this factor should be considered in rerouting decision. Since all factors are different measurements, we use the coefficient of variation instead of standard deviation to compute the variability for each factor.

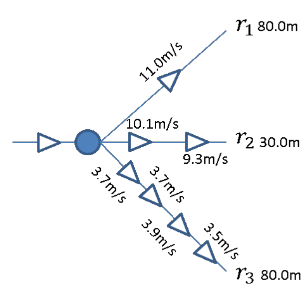

Fig. 5. An example of weight values allocation calculation in a-NRR

In the example shown in Figure 5, when a vehicle is approaching a junction, it has three road choices to follow: r_1, r_2 and r_3. To calculate the road occupancy RO factor, we assume that all vehicles have the same length (4.5 m) and the same minimum gap with each other (2.0 m). By knowing the actual length of those three roads, RO for all roads is calculated as $RO_1 = \frac{1\times6.5}{80.0} = 8.125\%$; $RO_2 = \frac{2\times6.5}{30.0} = 43.33\%$; $RO_3 = \frac{4\times6.5}{80.0} = 32.5\%$.

The second factor (i.e. estimated travel time TT) is calculated as the ratio of the road length to its average instantaneous travelling speed. When there is no vehicle running on this road, the average speed is replaced by the maximum allowed

TABLE I
MAPS STATISTICS

	Beijing (Asia)	Cape Town (Africa)	London (Europe)	Los Angeles (North America)	Rio de Janeiro (South America)	Sydney (Australia)
#roads<300m / #all roads	89.31%	95.84%	98.27%	94.21%	96.14%	97.43%
#Junctions	28428	33689	149012	25363	30926	34165
#Roads	53076	81780	305824	60806	66363	75766
#Roads / #Junctions	1.87	2.43	2.05	2.40	2.15	2.22
Average road length (m)	138.04	94.51	57.90	115.08	96.80	78.01
Area (km^2)	1235.51	646.03	865.24	864.68	572.37	404.41
World Congestion Ranking	15	55	16	10	3	21

speed in this calculation. In this case, the calculations are as follows: $TT_1 = \frac{80.0}{11.0} = 7.27s$; $TT_2 = \frac{30.0}{(10.1+9.3)/2} = 3.09s$; $TT_3 = \frac{80.0}{(3.7+3.7+3.9+3.5)/4} = 21.62s$.

The third factor is the estimated remaining travel distance TD for which the calculation in a-NRR is shown in Section IV-D. Here, we just give these three values: $TD_1 = 1300m$, $TD_2 = 900m$, $TD_3 = 600m$;

The coefficient of variation CV is the ratio of standard deviation to the mean value. In this case, we get the following CVs for all three factors: $CV(RO) = 0.53$, $CV(TT) = 0.74$, $CV(TD) = 0.31$. Their summation is 1.58. Then we get the following weight allocation: $w_{RO} = \frac{CV(RO)}{1.58} = 0.333$; $w_{TT} = \frac{CV(TT)}{1.58} = 0.472$; $w_{TD} = \frac{CV(TD)}{1.58} = 0.195$.

Notice that the summation of these weight values is always equal to 1.

C. Adaptive selection of the operational parameters

The NRR-enabled local areas (agents), which are the operational parameters of NRR, aim at achieving the best trade-off between system cost and traffic improvement. In our previous work [3], the evaluation results on grid maps reveal that with the increase of the number of NRR-enabled local areas, the improvement of traffic performance increases sharply up to the peak value when 5 agents are enabled, then slowly decreases. Therefore, the operational cost is proportional to the number of activated NRR agents.

However, enabling 5 local areas/agents cannot guarantee that the peak value will be reached under any traffic conditions and urban scenarios. In order to find the most suitable agents to be enabled, traffic managers need to tune NRR with several trials manually according to various traffic and closed road locations. The extra cost raised from this process could potentially prevent NRR to be applied in future smart cites.

The previous version of NRR chooses this parameter based on the closed road location. It assumes that the closed road is the center of en-route congestion distribution. It then chooses the agent that contains the closed road first, if the achieved traffic improvements are not sufficient it enables all its neighboring agents until reaching a satisfactory traffic improvement. However, its underlying assumption is not always right and the number of agents will increase exponentially, making the selection more inaccurate. To solve these two problems, based on the philosophy of NRR, we believe that if a certain local area does not have a roughly balanced traffic load, then

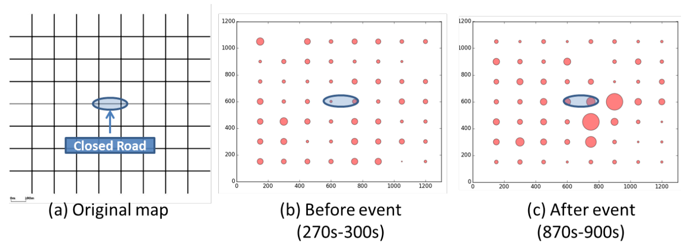

Fig. 6. The geographical distribution of standard deviations (STD) of a set of RO values from all outgoing roads in each agent: before and after the occurrence of an event on the central road in 8X7 grid map scenario. The larger the circle is, the larger value of STD a certain agent has.

we need to execute NRR. Thus, this selection process deals directly with the cause of congestion without any dependence on the weak assumption of closed road.

Therefore, the key question is how a-NRR can determine whether a given local area has a balanced traffic load or not. To solve this problem, K-means [17] algorithm is applied in a-NRR. First, for each local area with at least two outgoing roads, the TOC of a-NRR calculates and updates the standard deviation STD of RO of all outgoing roads periodically, then k-means is applied to generate (k=2) two clusters in each time interval. One cluster has relatively smaller STD while the other has larger STD. The latter cluster of local areas needs to enable NRR because larger STD means such agent does not have roughly balanced traffic load. Let us consider the example shown in Figure 6 where in 1800secs simulation test, we close the central road of 8X7 grid map (Figure 6.a) from 300th to 1500th sec. From Figure 6.b we observe that all agents have similar small STD before the beginning of the road closure. 600s after the occurrence of an event, we can see from Figure 6.c that only few agents located in the vicinity of the closed road have much larger STD. It is, therefore, difficult to determine a threshold separating the small amount of agents with large STD from the large number of agents with small STD, but k-means algorithm, as a typical clustering algorithm, can easily achieve this with low computation cost because in this case k=2 and only one-dimension input data is used.

D. Improved routing cost function

a-NRR maintains the same framework of the routing cost function we used previously in s-NRR with one major improvement in the estimation of remaining travel distance. Since road topologies do not change so often, instead of calculating this distance on-line using Euclidean distance as in s-NRR, a-NRR pre-computes the actual shortest path cost for all possible O/D pairs in a certain map and stores this information in the memory before computing the rerouting decision. Because urban road networks are sparse graph in which the number of roads is significantly smaller than the square of the number of junctions, we use repeated one-to-all Dijkstra's Algorithm rather than Floyd-Warshall algorithm to generate a file of all O/D pairs' shortest path cost.

Notice that a-NRR does not consider angle similarity (i.e. the closeness to en-route congestion) because it is based on the same above weak assumption (i.e. the closed road should be in the center of the congestion distribution).

V. EVALUATION METHODOLOGY

A. Simulation settings

In this study, the latest version (0.23.0) of SUMO [18] combined with TraCI [19] is the simulation platform used to carry out the performance evaluation of our proposed system. All the solutions used for comparison purpose are implemented in Python 2.7. An 1800 seconds duration of city center subset of TAPASCologne [20] scenario is used in our simulation. To mimic the occurrence of an en-route event, we close two roads (i.e. a bidirectional road segment), as shown in Figure 7, for 1200 s from the 300th to the 1500th sec. Notice that the trip generation process lasts for 1800 sec but the whole simulation runs until all trips are finished.

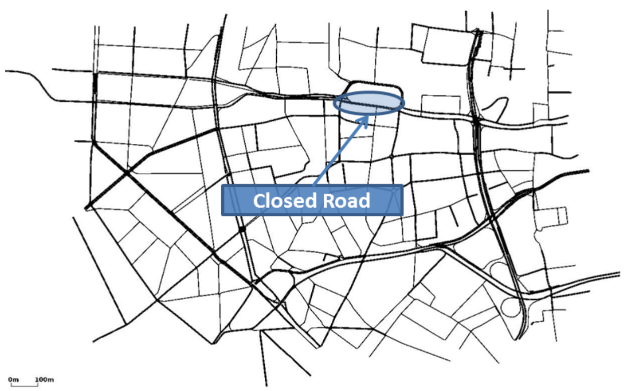

Fig. 7. Location of closed roads in city center area of TAPASCologne

B. Traffic measurements

In general, we evaluate the performance of vehicle rerouting systems in two types of traffic measurements: travel time and travel time reliability.

- Travel time is the amount of time a vehicle needs to finish its trip from origin to destination.
- The average travel time consists in evaluating the performance of the whole road network for all measured vehicles' trip times.

TABLE II
PERFORMANCE EVALUATION RESULTS

	ATT(sec)	TTI	95PTT(sec)	PTI	SS	TTL(km)
ORG	140.90	1.40	269.75	2.70	0.74	4483.79
ERE	214.88	2.11	705.50	6.91	3.32	4483.79
FasRe	216.10	2.12	711.75	6.97	3.34	4486.05
ShoRe	227.69	2.25	746.75	7.37	3.43	4485.55
s-NRR	172.55	1.68	411.0	3.99	2.49	4498.26
s-NRR-v	146.06	1.43	291.0	2.84	0.86	4515.03
a-NRR	146.11	1.42	290.75	2.83	0.78	4528.24

ATT: average travel time; 95PTT: 95th percentile travel time;
SS: system stability; TTL: total travel length

- Free flow travel time is the amount of time a vehicle is expected to spend using the maximum allowed speed to traverse a given route.
- Travel time index (**TTI**), similar to INRIX index [2] and TomTom index [16], measured for all the trips is the ratio of total travel time to total free flow travel time.
- Travel time distribution is a log-normal distribution with duration per single trip as the x-axis and the y-axis is the number of trips within a particular trip duration range.
- Travel time reliability is defined as the probability of on-time arrival of drivers for a single or multiple trips.
- In practice, it is measured by the planning time index (**PTI**) which is the ratio of 95th percentile travel time (i.e. 95% of trips have shorter travel time than it or only 5% of trips have longer travel time than it) to the average free flow travel time.

Other measurements considered in this paper are travel length and system stability. The total travel length serves as a metric to check whether the rerouting system chooses a much longer route to achieve shorter trip time or not, while the system stability is used to evaluate the stability of spatial and temporal traffic load distribution. A lower value (i.e. standard deviation) of the system stability implies that the traffic is more balanced.

VI. EVALUATION RESULTS AND ANALYSIS

In this section, we firstly show how much traffic improvements s-NRR gains by introducing VANETs technology. Then, we compare the performance of a-NRR against our previous s-NRR and the widely-used VNS. All main results are outlined in Table 2 in which **ORG** refers to the original scenario where no en-route event has occurred and no rerouting system is applied, while **ERE** represents an en-route event scenario as described in Section V-A but no rerouting system is applied.

A. S-NRR V.S. S-NRR WITH VANETS

s-NRR: The same version of static-NRR described in Section III, which is a SCATS-based implementation of [3]. Specifically, we evenly assign each weight value of the routing cost function in this version. We also only enable local areas that are controlled with traffic lights because in the real world (24 local areas in total in our testing scenario of Cologne), the induction loops are only deployed in such local areas. The update frequency is set to its highest value of 60s. Notice that the road occupancy in s-NRR is an aggregated value calculated as the percentage of time a loop detector is occupied by vehicles in the past 60s.

s-NRR-v: This is the version of s-NRR with the replacement of induction loops by VANETs. Specifically, we enable all local areas (389) because wherever vehicles are running VANETs coverage is ensured. Additionally, for the sake of simplicity of simulation, we set the update frequency of traffic information to 1s (i.e. 60 times faster than s-NRR) although the slowest update frequency of beacons in VANETs is 10 times per second. Notice that s-NRR-v is an imaginary scenario aiming to show the benefits that VANETs can bring to s-NRR.

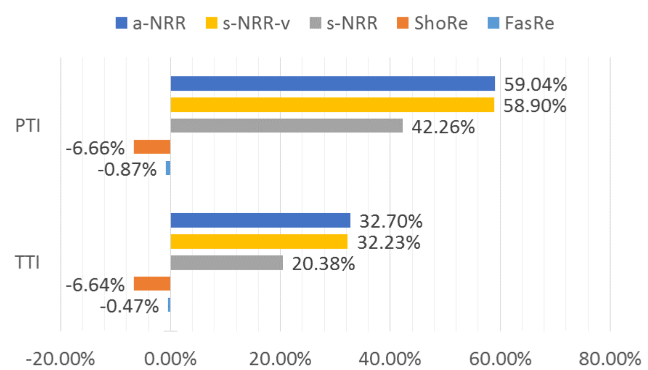

Fig. 8. Improvements of FasRe, ShoRe, s-NRR, s-NRR-v and a-NRR in terms of TTI and PTI against ERE scenario

We can see clearly from Figure 8 that replacing induction loops by VANETs allows s-NRR to further reduce the achieved PTI by 16.64% and the TTI by 11.85%. From Table 2 we learn that this performance improvement is due to the achieved more balanced traffic as witnessed by the substantial increase in system stability (65.46%) at the expense of an increase of 0.37% only in travel length, compared to s-NRR. From Figure 9 we can see that s-NRR-v nearly halves the maximum travel time compared to s-NRR, which means improving the fairness and significantly reducing the travel time for most of the vehicles.

B. VNS, S-NRR AND A-NRR

In general, drivers become aware of an event occurred ahead when they are one junction away from the closed road, thanks to their own observation or temporary notification signs. We distinguish two common cases where drivers use VNS to bypass such unexpected congestions:

FasRe: Based on updated traffic information which marks the closed road with very low speed already, VNS uses typical selfish routing algorithm (i.e. DA or A*) to suggest a "fastest" (without considering future traffic changes) route.

ShoRe: Due to the fact that VNS does not have real-time traffic information update (frequency of 2-5 mins) and this information has limited coverage (only arterial roads are covered), drivers tend to use the route with the shortest distance provided by VNS as it has much faster response time than FasRe.

According to Table 2 and Figure 8, although VNS (both FasRe and ShoRe) almost does not cause any increase in travel distance, it has even worse impact on traffic conditions than doing nothing (i.e. ERE) in the face of unexpected congestions. FasRe causes nearly 7% degradation in terms of PTI and TTI. This is the typical case of overusing selfish routing as stated in [7] with Baress's Parodox. From Figure 9 we can learn that VNS almost changes the shape of a typical trip duration distribution (log-normal) by extending the right tail and makes more vehicles have relatively longer travel time.

The implementation of **a-NRR** fits its description as presented in Section IV. Additionally, to make a-NRR more energy and bandwidth efficient and considering the fact that road traffic conditions would not change dramatically within very short time periods (i.e. about 1s), we set the update frequency to every 10 s, which is 10 times slower than s-NRR-v, but still 12 and 6 times faster than the fastest VNS and s-NRR, respectively. For k-means algorithm, we set k=2 because we only need the agents with relatively unbalanced traffic load; the number of iterations is 20 as it is the default setting of the Python library-Scipy and it still runs very fast as well.

With only 0.99% travel length increase, a-NRR can achieve the best traffic improvements among all other rerouting systems. It reduces PTI and TTI by 59.04% and 32.70% respectively compared to ERE and nearly recovers the traffic conditions in terms of PTI and TTI to its state in ORG where no event has occurred. We can also observe this improvement from the very low and similar system stability compared with ORG, proving that this improved traffic conditions are achieved by properly balancing the traffic load with a-NRR. Compared to the SCATS-based implementation of our previous work s-NRR, a-NRR further decreases PTI and TTI by 17.78% and 12.32% respectively, implying that it is worth to upgrade s-NRR to a-NRR. Figure 9 also shows that a-NRR basically maintains the original shape of distribution of travel time duration with reasonable longer right tail, considering those unlucky vehicles that are trapped into the closed road and could not get out. The number of enabled NRR agents in s-NRR is 24 while in a-NRR it ranges from 33 to 107 with a mean of 77.70 and a median equals to 78. Therefore, a-NRR has increased the operational cost as well but compared to s-NRR-v (389 enabled agents) this cost is still acceptable. Moreover, although s-NRR-v shows similar traffic improvements as a-NRR, due to its huge operational cost (all enabled agents and 10 times faster but with unnecessary high update frequency to track the road-based traffic movement), a-NRR is still the most efficient system we suggest to use.

VII. CONCLUSION AND FUTURE WORKS

This paper builds on our previous preliminary idea of next road rerouting (NRR) and extends it to deal efficiently with unexpected road traffic congestions resulting from en-route events. By using VANETs as a provider of real time traffic information, the new designed system called adaptive-NRR (a-NRR) can automatically adjust its algorithmic and

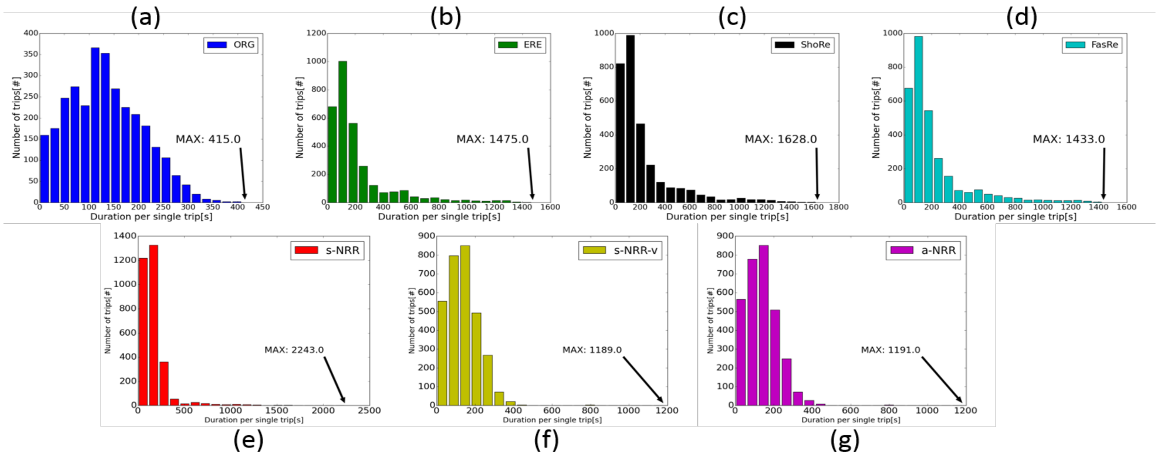

Fig. 9. Trip duration distribution of ORG, ERE, ShoRe, FasRe, s-NRR, s-NRR-v and a-NRR in the city center of TAPASCologne Scenario

operational parameters according to traffic changes in real-time to further alleviate the congestion. In the city center area of TAPASCologne, the obtained simulation results show that a-NRR can significantly reduce the travel time and improve travel time reliability, compared to static-NRR and the widely-used vehicle navigation systems.

As a future work, we plan to validate the effectiveness of a-NRR using more scenarios if more datasets become available in SUMO community. We also believe that it would be more beneficial to investigate new ways to reduce the number of enabled agents by improving the efficiency of the applied clustering algorithm (e.g. k-means in a-NRR).

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